

Correlation Analysis of Duty Cycle Effects on Exhaust Emissions and Fuel Economy

by Jun Tu, W. Scott Wayne, and Mario G. Perhinschi

Correlation analysis was performed to investigate the effects of drive cycle characteristics on distance-specific emissions (g/mile) and fuel economy (mpg) and consequently determine the most influential cycle metrics for modeling. A detailed analysis of linear and non-linear correlations was performed among cycle metrics to avoid collinearity and reduce the number of variables. The order of importance of the selected cycle metrics was determined. Results show that average speed with idle, number of stops per mile, percentage idle, and kinetic intensity were the most important cycle metrics affecting emissions and fuel economy. Preliminary regression analysis reinforced their importance for emissions modeling purposes.

INTRODUCTION

West Virginia University (WVU) has been engaged in developing an Integrated Bus Information System (IBIS) (Wayne et al. 2011) for the Federal Transit Administration (FTA). The intent of IBIS is to provide information on emissions and fuel economy for available bus technologies for bus procurement activities. IBIS includes a database of emissions test results of transit buses, a bus fleet emissions model, and a life cycle cost model. Compared with existing major emission models, such as the Mobile Source Emission Factor Model (MOBILE6) (U.S EPA 2003), the Motor Vehicle Emission Simulator (MOVES) developed by the U.S. Environmental Protection Agency (U.S. EPA 2010), IBIS provides transit agencies a simple tool to satisfactorily estimate emissions for evaluating the impact of new vehicle procurement on the overall fleet emissions profile. Similarly, IBIS is simpler compared with the Emission FACTors (EMFAC) model developed by the California Air Resources Board (CARB 2006).

The purpose of this study is to investigate the drive effects of cycle characteristics, which are metrics based on second-by-second vehicle speed data and distance-specific emissions in order to identify the most important parameters that should be included in a predictive emissions model. These emissions are carbon monoxide (CO), carbon dioxide (CO₂), oxides of nitrogen (NO_x), hydrocarbons (HC), and particulate matter (PM). This study is unique because WVU collected emissions data from 12 predefined vehicle speeds on the same vehicle using a chassis dynamometer. These speeds are the chassis dynamometer test cycles used in this study and are different from test or duty cycles in which a driver operates a bus on a chassis dynamometer to perform emissions testing. Data interpolation enabled the authors to investigate the statistical relationships between cycle metrics and their impacts on emissions and fuel economy (FE). In previous studies, data from only a limited number of test cycles on the same vehicle (typically five or less) were available, and this limited the effectiveness of their statistical analyses. This study identifies the most influential cycle metrics for inclusion in the IBIS emissions model as well as other emissions and fuel economy modeling efforts.

Driving characteristics are among the main factors affecting emissions and fuel economy of transit buses. Other important factors include vehicle parameters, fuel types, engine parameters, road conditions, and ambient conditions (Clark et al. 2002). To mimic actual driving conditions of on-road vehicles, chassis dynamometer cycles have been developed (Gautam et al. 2002, Nine et

al. 1999). Previous studies, using emissions data from multiple test cycles, showed that distance-specific emissions depended strongly upon the characteristics of duty cycles and found that average speed was one of the most important cycle metrics (Graboski et al. 1998, Nine et al. 2000, Clark et al. 1997, Vora et al. 2004). The MOBILE6 and EMFAC models estimate emissions as a function of average speed. Specifically, these macroscopic models calculate emissions based on average speed and vehicle miles traveled. At different average speeds, the study used speed correction factors to estimate emissions. These speed correction factors are determined by fitting emissions values with average speed. Previous studies showed the insufficiency of using average speed to evaluate emissions since average speed alone could not comprehensively reflect cycle characteristics (Ahn et al. 2002, Rakha and Ding 2003). Other metrics besides average speed, such as percentage idle and average acceleration, have been investigated (Andre and Pronello 1997, Wayne et al. 2007, Clark et al. 2007, Khan et al. 2007, Rakha and Ding 2003). However, these studies did not discuss all important duty cycle metrics.

Thirteen cycle metrics were considered in this study. They are average speed with idle (or average speed) and without idle, number of stops per mile (stops/mile), percentage idle, standard deviation of speed with and without idle, average and maximum acceleration, average and maximum deceleration, aerodynamic speed, which is the difference between average cubed speed and average speed, kinetic intensity, and characteristic acceleration (O'Keefe et al. 2007). The latter, characteristic acceleration, is specific kinetic energy per unit mass and distance required accelerating a vehicle over a duty cycle after ignoring road grade effects. This acceleration is equal to the actual vehicle acceleration if the vehicle increases its speed at a constant rate. The square of aerodynamic speed directly reflects the effects of aerodynamics on fuel economy and it is equal to the actual vehicle speed from driving at a constant speed. Kinetic intensity relates to fuel savings of hybrid vehicles over their conventional counterparts tested on the same cycles, and it gives an indication of whether hybridization will result in fuel savings for a particular duty cycle. Kinetic intensity is the ratio of characteristic acceleration to the square of aerodynamic speed. A cycle with a larger characteristic acceleration and a smaller aerodynamic speed that results in higher kinetic intensity is better for hybridization (O'Keefe et al. 2007).

These 13 cycle metrics were analyzed by correlation to reduce the number of cycle metrics and remove those that are collinear. In selecting the metrics to use in the IBIS emissions model, the study considered the abilities of transit agencies to calculate their values using data available to them. In some cases, some metrics were retained or eliminated based on this additional criterion. To account for non-linear relationships, this study uses a non-parametric correlation analysis to determine the order of importance of the chosen metrics in predicting emissions and fuel economy. Preliminary regression analysis was performed to demonstrate and reinforce the significant effect of the selected cycle metrics for modeling. The JMP® statistical software (SAS Institute 2009, Freund et al. 2003) and MATLAB® were used for the data analysis, as well as correlation and regression analysis in this study.

TEST VEHICLE INFORMATION

A model year (MY) 2000 Orion diesel transit bus was tested at the Washington Metropolitan Area Transit Authority (WMATA) facility to compare the effects of different drive cycles on emissions. The bus had a gross vehicle weight rating (GVWR) of 42,540 pounds and a curb weight (the weight of a bus without passengers but with all of standard equipment) of 28,800 lbs. The weight as tested was 33,300 pounds, representing half-seated passenger load. The test bus was powered by a 2000 MY, 8.5-liter, 4-cylinder, and 275 horsepower Detroit Diesel S50 engine with a diesel oxidation catalyst (DOC). The fuel used by the bus was type one ultra-low sulfur diesel (ULSD1). The vehicle was equipped with a four-speed Voith D863 automatic transmission. The vehicle configuration

remained the same for all test cycles. The bus was tested over 12 test cycles, which are described in the following section.

TEST CYCLES

Multiple chassis dynamometer test cycles (Clark et al. 2002, DieselNet 2007, SAE International 1982, SAE International 2002, Schiavone et al. 2002, Thompson et al. 1990, Wayne et al. 2002) were used since emissions and fuel economy are related to duty cycles. Since it is not practical to develop test cycles for all types of vehicles and driving behaviors, it is necessary to develop a limited but representative number of test cycles to mimic driving activities of realistic transit bus operation. Specific test cycles were generated to represent real-world operation in specific applications or localities. For example, the New York Bus cycle (NYBus) (Clark et al. 2002) was developed to represent the driving conditions of heavy-duty vehicles in New York City. The test vehicle was operated through 12 chassis dynamometer cycles for this study, and multiple repeat runs were performed on certain test cycles. In total, 13 cycle metrics were considered in this study. The test cycles and their characteristics are summarized in Table 1 and cycle abbreviations are defined in Appendix A at the end of this paper.

EXTENDED DATABASE

Since only 12 cycles were available for analysis, an expanded database was desired. Figure 1 shows carbon monoxide emissions as a function of cycle average speed ranging from the lowest speed of 3.57 miles per hour (mph) (NYBus cycle) to the highest speed of 43.72 mph (COMM cycle) (SAE International 1982). No test cycles existed between an average speed from 28.63 mph (ETC cycle) (DieselNet 2007) and 43.72 mph (COMM cycle). Interpolation was used to extend the database to fill the gaps as mentioned above with the assumption that no extreme cycle characteristics exist between adjacent cycle points. Initially, 18 cycle points were interpolated using an equal interval of two mph for the average speed. A piecewise cubic hermite interpolating polynomial (pchip) (Kahaner et al. 1988) was applied in this study using MATLAB®. The pchip polynomial is one type of piecewise cubic polynomials and it can be determined using both values from end-points and their derivatives. A comparison with other interpolation methods is provided in Figure 1. Compared with linear interpolation, pchip interpolation is smoother and less likely to overshoot. Although spline interpolation had smoother results than pchip, it was not considered because it caused more oscillation in data interpolation. The same analysis and method were applied to the four other cycle metrics. The magnitudes of the intervals were 10% for percentage idle, four stops per mile (stops/mile), three mph for standard deviation of speed, and one reciprocal of unit mile (mile⁻¹) for kinetic intensity. In this way, 44 cycle points were generated to extend the database to 56 cycle points. When extended emissions and fuel economy data were plotted against duty cycle metrics, no significant deviation from the reference dataset was observed and the interpolated cycle points followed the same trend as the reference points.

ROAD LOAD DERIVED CYCLE METRICS

Unlike conventional cycle metrics derived directly from speed-time trace (second-by-second vehicle speed data), aerodynamic speed, characteristic acceleration, and kinetic intensity were derived from a road load equation (Gillespie 1992, Miller 2004) to relate them to fuel consumption (O'Keefe et al. 2007). The general form of the road load equation is:

$$(1) \quad F_{\text{traction}} = M \frac{dv}{dt} + F_{\text{aero}} + F_{\text{rolling}} + F_{\text{grade}}$$

Table 1: Statistics of 12 Target Dynamometer Test Cycles

Cycle	Duration (seconds)	Distance Traveled (miles)	Average Speed with Idle (mph)	Average Speed without Idle (mph)	Percentage Idle	Number of Stops per Mile	Standard Deviation of Speed with Idle (mph)	Standard Deviation of Speed without Idle (mph)
ART	291.6	2.00	24.71	29.55	16.39%	2.00	15.64	12.19
BEELINE	1724	6.79	14.17	19.29	26.54%	3.54	14.74	14.04
BRAUN	1750	6.73	13.85	18.48	25.04%	4.31	11.35	9.30
CBD	586	2.01	12.36	15.71	21.35%	6.96	8.46	6.19
COMM	329.6	4.00	43.72	49.71	12.04%	0.25	19.46	11.46
ETC_12	1200	9.54	28.63	29.93	4.32%	0.42	15.84	14.95
MAN	1098.7	2.07	6.77	10.66	36.52%	9.68	7.33	6.56
NYBUS	620	0.61	3.57	10.69	66.60%	17.89	6.41	6.86
NY-COMP	1029	2.51	8.77	12.85	31.76%	7.58	9.44	8.84
OCTA	1950	6.54	12.08	15.52	22.17%	4.74	10.33	9.14
UDDS	1060	5.54	18.83	28.04	32.84%	2.89	19.82	18.07
WMATA	1839	4.25	8.32	13.47	38.27%	6.12	10.31	10.14

Cycle	Average Acceleration (ft/sec ²)	Maximum Acceleration (ft/sec ²)	Average Deceleration (ft/sec ²)	Maximum Deceleration (ft/sec ²)	Aerodynamic Speed (mph)	Characteristic Acceleration (ft/sec ²)	Kinetic Intensity (mile ⁻¹)
ART	2.02	3.67	6.45	7.33	35.58	0.65	1.26
BEELINE	2.06	7.33	2.58	10.27	32.03	0.88	2.10
BRAUN	2.08	8.07	2.80	11.73	24.17	0.72	3.02
CBD	2.87	3.67	6.38	7.33	18.55	0.57	4.04
COMM	1.37	3.67	6.67	18.33	52.84	0.15	0.14
ETC_12	1.14	13.20	1.26	8.07	39.16	0.31	0.50
MAN	2.04	7.33	2.59	8.80	15.78	0.94	9.24
NYBUS	4.09	9.53	2.39	7.33	16.64	1.25	11.07
NY-COMP	1.72	13.93	1.94	13.20	20.69	0.77	4.42
OCTA	1.88	5.87	2.61	8.07	22.10	0.72	3.60
UDDS	1.78	8.80	1.99	8.07	42.49	0.50	0.68
WMATA	1.74	4.40	2.10	6.60	23.22	0.77	3.51

Where $F_{traction}$ is the total traction required for vehicle motion, M is vehicle mass, dv/dt is vehicle acceleration, F_{aero} is aerodynamic resistance, $F_{rolling}$ is rolling resistance, and F_{grade} is grade resistance due to a slope. A detailed derivation and background information are provided in O’Keefe et al. (2007) and Simpson (2005).

Originally, these three cycle metrics were to be used with fuel consumption to differentiate duty cycles as well as fuel savings for hybrid vehicles on a given duty cycle (O’Keefe et al. 2007). Since they are derived from a road load equation and are related to energy usage, these cycle metrics are hypothesized to have some relationships with emissions and fuel economy.

Table 2 presents correlations of the metrics with distance-specific emissions and fuel economy, and it shows all three metrics have significant correlations. The negative correlations between aerodynamic speed and emissions indicate that emissions increase with decreasing aerodynamic speed, while the positive correlation with fuel economy shows that fuel economy increases along with increasing aerodynamic speed. However, characteristic acceleration as shown in Table 2 has an inverse relationship with the emissions and fuel economy compared with aerodynamic speed, which makes sense because larger characteristic acceleration requires more kinetic energy to accelerate, indicating higher fuel consumption and increased emissions. Kinetic intensity shows the same but stronger correlation trend as characteristic acceleration (except with fuel economy) compared with the other two metrics.

Figure 1: Reference Cycles and Comparison of Interpolation Curves Based on Average Speed

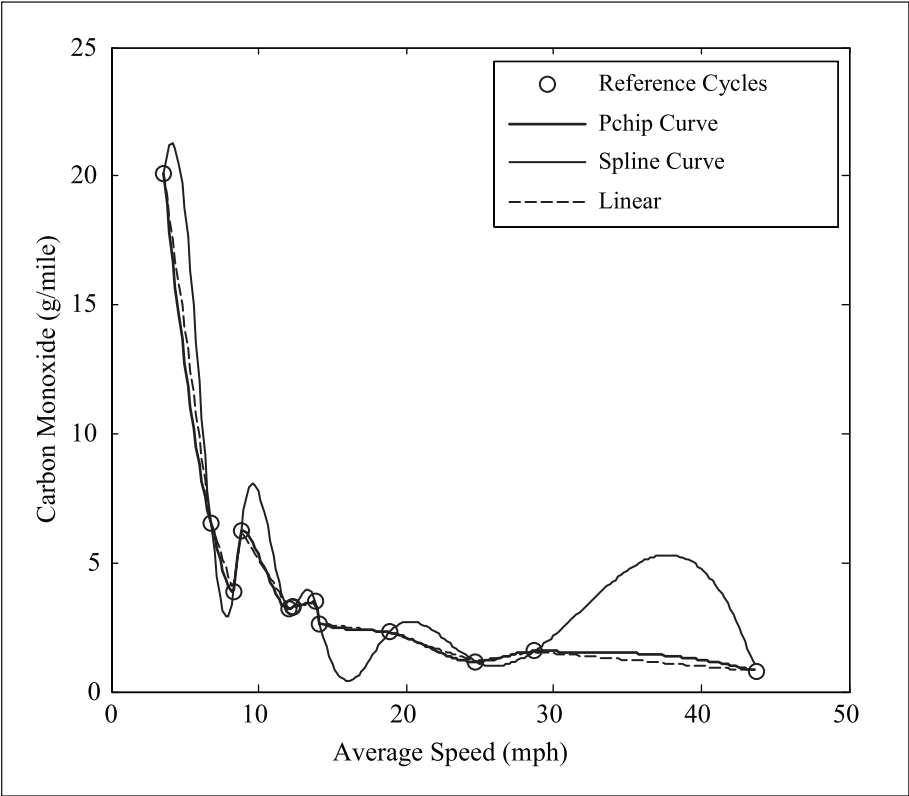


Table 2: Correlations of Road Load Derived Cycle Metrics With Emissions and Fuel Economy

	CO ₂	CO	HC	NOx	PM	FuelEco
AeroV	-0.77	-0.70	-0.80	-0.66	-0.72	0.85
CharAcc	0.89	0.78	0.79	0.82	0.81	-0.94
KInt	0.94	0.89	0.93	0.87	0.90	-0.84

Note: All correlations are significant at the 0.0001 level ($p < 0.0001$).

AeroV: Aerodynamic speed

CharAcc: Characteristic acceleration

KInt: Kinetic intensity

CO: Carbon monoxide

CO₂: Carbon dioxide

HC: Hydrocarbon

NOx: Oxides of nitrogen

PM: Particulate matter

FuelEco: Fuel economy

SELECTION OF THE IMPORTANT CYCLE METRICS

A detailed correlation analysis was performed to identify the duty cycle metrics having the most significant correlations with emissions and fuel economy and to detect highly correlated redundant metrics.

Correlation Analysis Among Cycle Metrics

A Pearson correlation matrix was applied to detect bivariate collinearity among the cycle metrics. The analysis shows that several variables highly correlate with each other. Although the existence of collinearity is not a violation of the assumptions of regression analysis, it shows that several cycle metrics have similar impacts on emissions and fuel economy and they should be removed from the analysis. Collinearity also makes it difficult to interpret the partial regression coefficients, which measure the effect of the corresponding cycle metrics while holding constant all other metrics. When collinearity exists, the affected coefficients estimate some effects for the response but not really from the corresponding metrics. Table 3 shows full correlation coefficients for the 13 duty cycle metrics. Statistically significant and strong correlations were found among some variables including the following:

- a. Average speed with idle versus average speed without idle, aerodynamic speed, and characteristic acceleration;
- b. Average speed without idle versus standard deviation of vehicle speed with idle, and aerodynamic speed;
- c. Stops per mile versus percentage idle and kinetic intensity;
- d. The standard deviations of vehicle speed with idle versus aerodynamic speed and standard deviation of vehicle speed without idle.

In total, nine pairs of metrics have correlations larger than 0.90 in absolute terms, which are statistically significant at probability levels of less than 0.0001. These pairs are highlighted with bold typeface letters in the lower triangular matrix in Table 3. Consistent with previous studies by Clark et al. (2002), Clark and Gajendran (2003), and Boriboonsomsin and Uddin (2006) that have concluded that average speed (with idle) is an important factor due to its relationship with other cycle properties, it is found that average speed with idle correlates with most cycle metrics. As a result, average speed without idle, aerodynamic speed, and characteristic acceleration were removed from the analysis. Average speed with idle was retained rather than average speed without idle because the former is easier for a transit agency to calculate. Similarly, the standard deviation of vehicle speed with idle has strong relationships with the standard deviation of vehicle speed without idle and aerodynamic speed, and it was retained, while the standard deviation of vehicle speed without idle was removed.

Aerodynamic speed correlates with both average speed and the standard deviation of vehicle speed, indicating that it may reflect the statistical features of vehicle speed such as the mean and dispersion. However, aerodynamic speed was removed, because average speed and standard deviation of vehicle speed were retained. Additionally, O'Keefe et al. (2007) showed that kinetic intensity is related to both aerodynamic speed and characteristic acceleration. Thus, it is better to retain kinetic intensity than aerodynamic speed or characteristic acceleration.

Since it reflects the transient nature of driving cycles and it is easily obtained, stops per mile were retained, as was the percentage idle because of its effects on emissions (Wayne et al. 2007), although both metrics strongly correlate with each other. However, this strong positive correlation cannot be well explained. For example, more stops in a trip do not necessarily mean a higher percentage of idling. If a short idle duration occurs at each stop, total idle time of that trip can be less than that of a trip with a longer idle duration at each stop and fewer total stops during the trip.

The strong correlation between kinetic intensity and stops per mile indicates that both metrics reflect some features of transient driving behavior.

Table 3: Correlations of All Cycle Metrics

	AspedWID	AspedWoID	PercID	Stops/Mi	VstdWID	VstdWoID	AveAcc	MaxAcc	AveDec	MaxDec	AeroV	CharAcc	KInt
AspedWID	1.00												
AspedWoID	0.98⁺	1.00											
PercID	-0.83 ⁺	-0.76 ⁺	1.00										
Stops/Mi	-0.83 ⁺	-0.82 ⁺	0.90⁺	1.00									
VstdWID	0.85 ⁺	0.90⁺	-0.69 ⁺	-0.87 ⁺	1.00								
VstdWoID	0.63 ⁺	0.67 ⁺	-0.54 ⁺	-0.76 ⁺	0.91⁺	1.00							
AveAcc	-0.66 ⁺	-0.60 ⁺	0.79 ⁺	0.82 ⁺	-0.63 ⁺	-0.57 ⁺	1.00						
MaxAcc	-0.08	-0.18	-0.08	0.08	-0.12	0.09	-0.25	1.00					
AveDec	0.43 ⁺	0.49 ⁺	-0.30 [*]	-0.29 [*]	0.31 [*]	-0.03	0.05	-0.74 ⁺	1.00				
MaxDec	0.51 ⁺	0.49 ⁺	-0.41 ^{**}	-0.33 [*]	0.28 [*]	0.00	-0.45 ⁺	0.16	0.22	1.00			
AeroV	0.94⁺	0.97⁺	-0.73 ⁺	-0.85 ⁺	0.97⁺	0.83 ⁺	-0.65 ⁺	-0.08	0.34 [*]	0.40 ^{**}	1.00		
CharAcc	-0.93⁺	-0.89 ⁺	0.88 ⁺	0.89 ⁺	-0.81 ⁺	-0.63 ⁺	0.79 ⁺	-0.04	-0.28 [*]	-0.47 ⁺	-0.87 ⁺	1.00	
KInt	-0.80 ⁺	-0.80 ⁺	0.82 ⁺	0.97⁺	-0.89 ⁺	-0.81 ⁺	0.73 ⁺	0.07	-0.29 [*]	-0.30 [*]	-0.85 ⁺	0.86 ⁺	1.00

Note:

* Correlation is significant at the 0.05 level

** Correlation is significant at the 0.01 level

+ Correlation is significant at the 0.001 level

AspedWID: Average vehicle speed with idle

AspedWoID: Average vehicle speed without idle

PercID: Percentage idle

Stops/Mi: Stops per mile

VstdWID: Standard deviation of vehicle speed without idle

VstdWoID: Standard deviation of vehicle speed with idle

KInt: Kinetic intensity

MaxAcc: Maximum acceleration

AveDec: Average deceleration

MaxDec: Maximum deceleration

AeroV: Aerodynamic speed

CharAcc: Characteristic acceleration

AveAcc: Average acceleration

Certain redundant metrics were retained because they could be easily calculated from basic route information available to transit agencies. The retention of these cycle metrics results in collinearity. However, a potential predictive model does not necessarily have to include all selected cycle metrics as explanatory variables. After some collinearity was removed, the total number of metrics decreased from 13 to nine.

Further Dimensionality Reduction

It is evident from Table 3 that the four-cycle metrics, including average acceleration (AveAcc), maximum acceleration (MaxAcc), average deceleration (AveDec), and maximum deceleration (MaxDec), have weak correlations with the other metrics. To be useful for emissions modeling, they must correlate with emissions and fuel economy. Table 4 shows the correlations of these four metrics with emissions and fuel economy. Average acceleration shows moderate and significant correlations while maximum acceleration, average deceleration, and maximum deceleration do not correlate well with the emissions and fuel economy.

Table 4: Correlations of Four Cycle Metrics vs. Emissions and Fuel Economy

	CO ₂	CO	HC	NO _x	PM	FuelEco
AveAcc	0.84 ⁺	0.81 ⁺	0.79 ⁺	0.84 ⁺	0.77 ⁺	-0.76 ⁺
MaxAcc	0.02	0.18	0.05	-0.09	0.24	0.14
AveDec	-0.25	-0.33*	-0.31*	-0.18	-0.33*	0.15
MaxDec	-0.32*	-0.27*	-0.30*	-0.34*	-0.22	0.30*

Note:

* Correlation is significant at the 0.05 level

+ Correlation is significant at the 0.001 level

CO: Carbon monoxide

CO₂: Carbon dioxide

HC: Hydrocarbon

NO_x: Oxides of nitrogen

PM: Particulate matter

FuelEco: Fuel economy

AveAcc: Average acceleration

MaxAcc: Maximum acceleration

AveDec: Average deceleration

MaxDec: Maximum deceleration

The effects of average deceleration on the metrics are less than the corresponding effects of average acceleration because the correlations are low. The main reason is that during deceleration an engine is often at idle, so deceleration activities do not increase or decrease emissions and fuel consumption. However, when a vehicle accelerates, more fuel is consumed, producing more emissions (Wang et al. 2000). In addition, maximum acceleration and deceleration do not correlate with emissions and fuel economy, possibly because both metrics correspond to single points in a cycle. Based on the above analysis, average deceleration, maximum acceleration, and maximum deceleration were removed from further consideration.

Thus, through the initial correlation analysis of 13 cycle metrics, six metrics were determined to be useful for emissions and fuel economy modeling, and seven were removed because they were either redundant or appeared to have little correlation with emissions and fuel economy. The selected six-cycle metrics retained are average speed with idle, percentage idle, stops per mile, standard deviation of vehicle speed with idle, kinetic intensity, and average acceleration.

DETERMINATION OF ORDER OF IMPORTANCE OF THE SELECTED CYCLE METRICS

The following section focuses on the effects of the six chosen metrics and their order of importance in emission and fuel economy. Non-parametric correlation and stepwise regression analysis were performed to evaluate their effects.

Non-parametric Correlation Between Selected Cycle Metrics and Emissions and Fuel Economy

As previously mentioned, if a nonlinear relationship actually exists between paired variables, Pearson's correlation will underestimate it. For example, in this study, the Pearson's correlation between carbon dioxide and average speed is -0.78 with a coefficient of determination of 0.60. The two variables have a power decay relationship, and this relationship exhibits a much better fit (*R*-square of 0.91) than the linear fitting (*R*-square of 0.60). Considering this, the non-parametric statistical correlation, Spearman's correlation, was used to evaluate the relationship accurately. The Spearman's correlation (ρ) is a rank correlation of the data and it does not require variables to be normally distributed nor linear. The meaning and range of ρ are essentially the same as that of Pearson's correlation with a zero value representing no correlation, one or minus one indicating a perfect positive or negative fit, respectively. A ρ between a zero and one means increasing X corresponds to increasing Y and vice versa, and ρ between a zero and minus one means increasing X corresponds to decreasing Y and vice versa.

The Spearman’s correlations between the six selected cycle metrics with emissions and fuel economy are in Table 5 together with their statistically significant levels. Average acceleration has the smallest correlation, making it the least important among the six selected metrics. Below is a detailed analysis for the importance of the other five metrics.

Table 5: Non-parametric Spearman’s Correlation

	CO ₂	CO	HC	NOx	PM	FuelEco
AspedWID	-0.9546	-0.965	-0.9208	-0.908	-0.9131	0.9558
PercID	0.9144	0.8674	0.8321	0.9172	0.8552	-0.9055
Stops/Mi	0.954	0.9665	0.9134	0.9033	0.9339	-0.9528
VstdWID	-0.8676	-0.8917	-0.8634	-0.8015	-0.8014	0.8729
AveAcc	0.6309	0.5441	0.5466	0.5833	0.5871	-0.6252
KInt	0.9537	0.9423	0.877	0.9032	0.9183	-0.9534

Note: All correlations are significant at the 0.0001 level (p<0.0001)

CO: Carbon monoxide	AspedWID: Average vehicle speed with idle	CharAcc: Characteristic acceleration
CO2: Carbon dioxide	PercID: Percentage idle	AveAcc: Average acceleration
HC: Hydrocarbon	Stops/Mi: Stops per mile	
NOx: Oxides of nitrogen	VstdWID: Standard deviation of vehicle speed with idle	
PM: Particulate matter	KInt: Kinetic intensity	
FuelEco: Fuel economy	AeroV: Aerodynamic speed	

Carbon Dioxide (CO₂) Emissions: The carbon dioxide emissions have the second strongest correlation with average speed with a coefficient of -0.9546, indicating that higher vehicle average speed results in lower carbon dioxide emissions. Actually, in addition to carbon dioxide, all other emissions have negative correlations with average speed. This shows that higher average speed produces lower emissions, which is consistent with previous findings (Wayne et al. 2007). Higher vehicle average speed involves fewer accelerations and decelerations, resulting in lower emissions. Stops per mile have the second largest correlation of 0.9540 followed by kinetic intensity with a correlation of 0.9537. Positive correlations imply that more stops per mile and higher kinetic intensity produce higher carbon dioxide emissions. Since the values of these three correlations are very close to each other, it is hard to tell which metric is most important for carbon dioxide emissions. Percentage idle and the standard deviation of vehicle speed have correlations of 0.9144 and -0.8676 with carbon dioxide emissions, respectively. The negative correlation shows that carbon dioxide emission decreases with increased standard deviation of vehicle speed. However, at the same average speed, increased standard deviation usually implies more transient cycle features, which produce higher carbon dioxide.

Carbon Monoxide (CO) Emissions: For carbon monoxide emissions, the variable stops per mile has the strongest positive correlation of 0.9665 with it, which is reasonable since carbon monoxide emissions in grams per mile are sensitive to the transient features of driving activities (Clark et al. 2002). The more stop-and-go features, the more deviations there are from a steady state, and the higher carbon monoxide emissions that are produced. Average speed has the second strongest correlation of -0.965 and kinetic intensity has a correlation of 0.942.

Hydrocarbon (HC) Emissions: Hydrocarbon emissions have the strongest correlation of 0.92 with average speed, followed by stops per mile of 0.91. The other correlations are below 0.9, indicating that stops per mile and average speed are the two most important metrics for hydrocarbon emissions.

Oxides of Nitrogen (NO_x) Emissions: Oxides of nitrogen emissions show the strongest correlation with percentage idle, which is consistent with the fact that excessive idle could produce more of it (Clark et al. 2002). It is also noticed that average speed, stops per mile, and kinetic intensity have strong correlations of 0.9 and above with oxides of nitrogen, indicating their significance in this type of emissions.

Particulate Matter (PM) Emissions: Particulate matter shows the strongest correlation of 0.93 with stops per mile. Particulate matter is also highly correlated with carbon monoxide (0.9246), reinforcing that both are sensitive to the transient features of driving activities. In addition, particulate matter has strong correlations above 0.9 with average speed and kinetic intensity.

Fuel Economy: Fuel economy strongly correlates with average speed with a correlation coefficient of 0.9558, indicating the higher the average speed the lower the amount of fuel consumed. It does not mean this trend would be consistent at much higher average speed levels. Previous studies showed that fuel economy reaches a maximum at a specific vehicle speed and decreases at higher average speeds as aerodynamic drag begins to dominate. The result is a parabolic curve (Wayne et al. 2007, Rakha and Ding 2003).

The order of significance of the six-cycle metrics' impacts on emissions and fuel economy are in Table 6. Strong, moderate, and weak correlations are defined as coefficients higher than 0.9, between 0.8 and 0.9, and below 0.8, respectively. Stops per mile and average speed have strong correlations with all emissions and fuel economy. This result is consistent with the common interpretation that average speed reflects cruise features of driving activities while stops per mile are linked to transient features. Emissions and fuel economy might reflect the effects of both cruise and the transient features of driving cycles. However, it is difficult to tell which metric is most important, because those in the strong correlation category have very similar correlation coefficients.

Table 6: Summary of Order of Importance for the Selected Six Cycle Metrics

Dependent Variable	Strong Correlation	Moderate Correlation	Weak Correlation
CO	Stops/Mi, AspedWID, KInt	VstdWID, PercID	AveAcc
CO ₂	Stops/Mi, AspedWID, PercID, KInt	VstdWID	AveAcc
HC	Stops/Mi, AspedWID	VstdWID, KInt, PercID	AveAcc
NO _x	Stops/Mi, AspedWID, PercID, KInt	VstdWID	AveAcc
PM	Stops/Mi, AspedWID, KInt	VstdWID, PercID	AveAcc
FuelEco	PercID, AspedWID, Stops/Mi, KInt	VstdWID	AveAcc

Note: Strong Correlation: ≥ 0.9 ; Moderate Correlation: ≥ 0.8 & < 0.9 ; Weak Correlation: < 0.8

CO: Carbon monoxide
CO₂: Carbon dioxide
HC: Hydrocarbon
NO_x: Oxides of nitrogen
PM: Particulate matter

FuelEco: Fuel economy
AspedWID: Average vehicle speed with idle
PercID: Percentage idle
Stops/Mi: Stops per mile
VstdWID: Standard deviation of vehicle speed with idle

KInt: Kinetic intensity
AeroV: Aerodynamic speed
CharAcc: Characteristic acceleration
AveAcc: Average acceleration

Regression Analysis

To validate the significant effects of the selected cycle metrics on emissions and fuel economy, regression analyses were performed with selected metrics as independent variables. The regression models are expressed as in Equation (2) and their coefficients are in Table 7.

$$(2) \quad y = a + \sum_{i=1}^5 b_i x_i + \sum_{i=1}^5 c_i x_i^2 + \varepsilon$$

where a is an intercept, b_i , and c_i are regression coefficients, ε is the residual term, and y is the dependent variables corresponding to emissions or fuel economy while x_i is the set of independent variables corresponding to the five selected cycle metrics in Table 6. Average acceleration was not considered due to its weak influence on the dependent variables. Squared terms for each of the selected cycle metrics were added to account for possible nonlinear relationships, and stepwise regression was employed to select the statistically significant variables to be used in the models.

Table 7: Regression Models Based on Selected Metrics

Term	CO ₂	CO	HC	NOx	FuelEco	PM
Intercept	507.715	-0.017	0.193*+	3.236	6.730*+	-0.207*
AspedWID	15.492**	-	-	0.276*+	-0.046+	-
PercID	3268.232*+	-	0.138*+	46.742*+	-9.523*+	-
(PercID-0.268)*(PercID-0.268)	-6125.302*+	-	0.426*+	-	31.291*+	-
Stops/Mi	111.860**	0.673*+	-	0.286	-0.116	0.068*+
(Stops/Mi-5.20683)*(Stops/Mi-5.20683)	12.603*+	0.068*+	-	0.069*+	-0.017**	0.001**
VstdWID	17.135	-	-0.008*+	-0.132	0.060	0.014*
(VstdWID-12.8037)*(VstdWID-12.8037)	-11.253*+	-	0.001*+	-0.070**	0.021*+	-
KInt	73.522+	0.052	-	0.508*	-	-
(KInt-3.58075)*(KInt-3.58075)	-	-0.060+	-	-	-	-
Adjusted R ²	0.99	0.98	0.96	0.98	0.98	0.94
RMSE	86.15	0.52	0.01	1.07	0.22	0.07

Note:

* Significant at the 0.05 level

** Significant at the 0.01 level

+ Significant at the 0.001 level

*+ Significant at the 0.0001 level

RMSE: Root mean square error

CO: Carbon monoxide

CO₂: Carbon dioxide

HC: Hydrocarbon

NOx: Oxides of nitrogen

PM: Particulate matter

FuelEco: Fuel economy

AspedWID: Average vehicle speed with idle

PercID: Percentage idle

Stops/Mi: Stops per mile

VstdWID: Standard deviation of vehicle speed with idle

KInt: Kinetic intensity

AeroV: Aerodynamic speed

CharAcc: Characteristic acceleration

The results were compared with regressions based on average speed as shown in Table 8. For each response variable, average speed-based power regressions give larger R -squared values and smaller root mean square errors (RMSE) compared to linear, polynomial, power, exponential, and logarithmic regressions. All R -squared values are greater than 0.85, except for 0.79 for oxides of nitrogen emissions, and the coefficients are statistically significant at the 0.0001 probability level ($p < 0.0001$). Compared with the average speed-based regressions in Table 8, the regression results based on multiple metrics in Table 7 show adjusted R -squared values above 0.95, except the 0.94

for particulate matter, which is good considering the transient dependency of particulate matter emissions. Most of RMSE values are substantially reduced (over half), except that of particulate matter.

Table 8: Average Speed Based Regressions

Response	Regression	R ²	RMSE
CO ₂	$y = 10021x^{-0.5343}$	0.91	306.74
CO	$y = 64.976x^{-1.147}$	0.94	1.18
HC	$y = 0.5402x^{-0.5258}$	0.86	0.02
NOx	$y = 66.8501x^{-0.4366}$	0.79	3.93
FuelEco	$y = x^{0.5298}$	0.91	0.60
PM	$y = 4.1171x^{-1.0262}$	0.90	0.10

Note:

RMSE: Root mean square error HC: Hydrocarbon FuelEco: Fuel economy
CO: Carbon monoxide NOx: Oxides of nitrogen
CO₂: Carbon dioxide PM: Particulate matter

Figure 2 compares the estimated and experimental values of emissions and fuel economy for the NYBus cycle based on the old models (regressions based on average speed) and the new models (based on selected multiple cycle metrics). For the NYBus cycle, the new models show over 75% less percentage errors for all responses. Figure 3 compares the mean percentage errors (MPE) using both models after considering all cycle points. It shows that on average the new models have more than 40% reduction in MPE for carbon dioxide, hydrocarbons, and fuel economy. It also shows that carbon monoxide and particulate matter have MPE above 15% for both models, further indicating it is difficult to predict them due to their high sensitivity to transient features of vehicle operation. If interaction terms of the selected cycle metrics or the appropriate transformations (such as the Box-Cox method) of response variables were considered in the analysis, the multiple parameter models might show further improvement.

The regression models developed herein were used to determine the impact of cycle metrics on emissions and fuel economy. The intent of this analysis was to select cycle metrics for the development of a transit fleet emission model for use by transit agencies during vehicle procurement and strategic planning. Therefore, comparison and validation against existing average speed-based models are not presented here. An overview of the completed transit fleet emissions model and comparison of model results with the speed factor based EPA Mobile6 and MOVES models are presented in Wayne et al. (2011).

Figure 2: Comparison of Old and New Models to NYBus Cycle Estimation

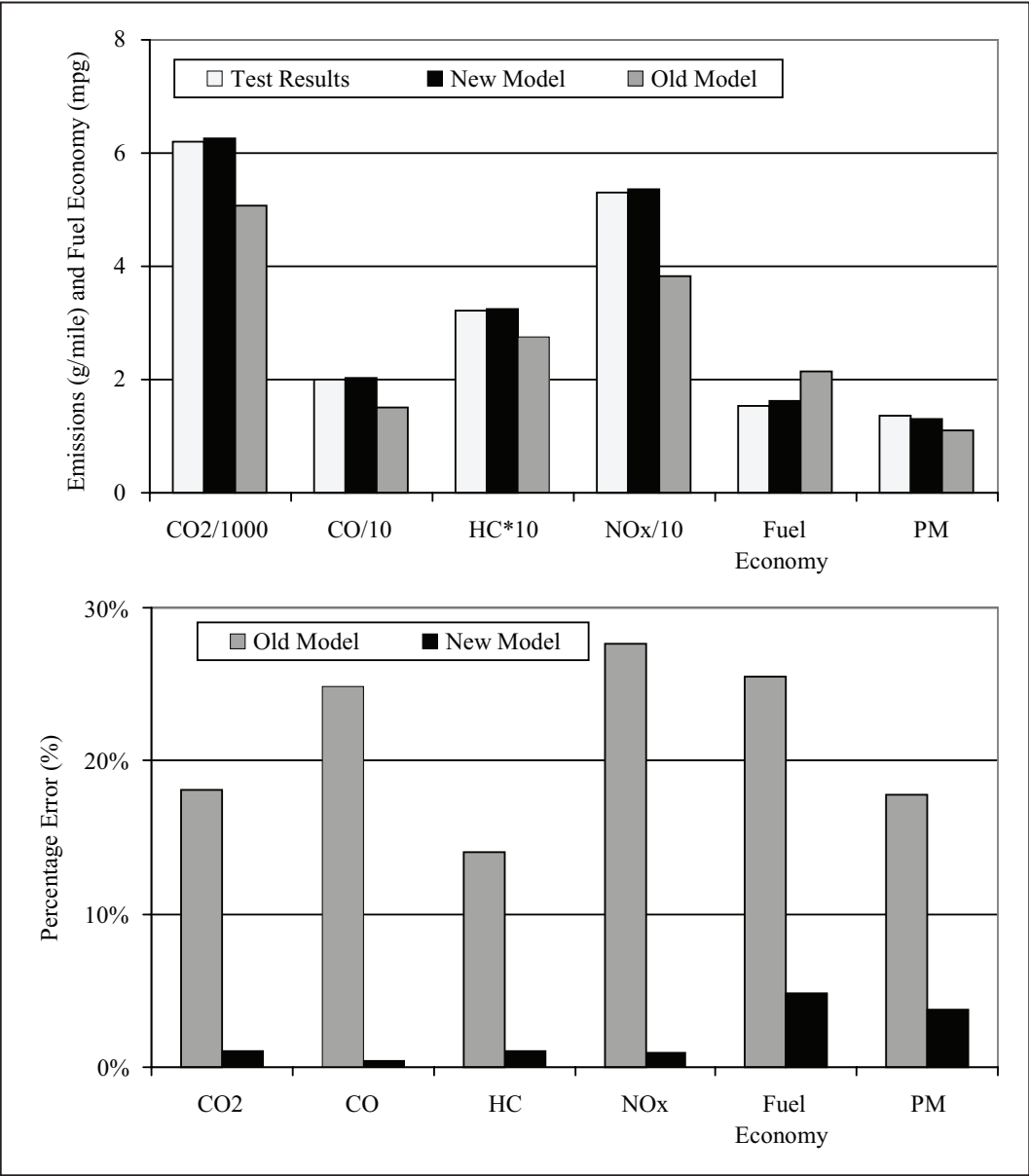
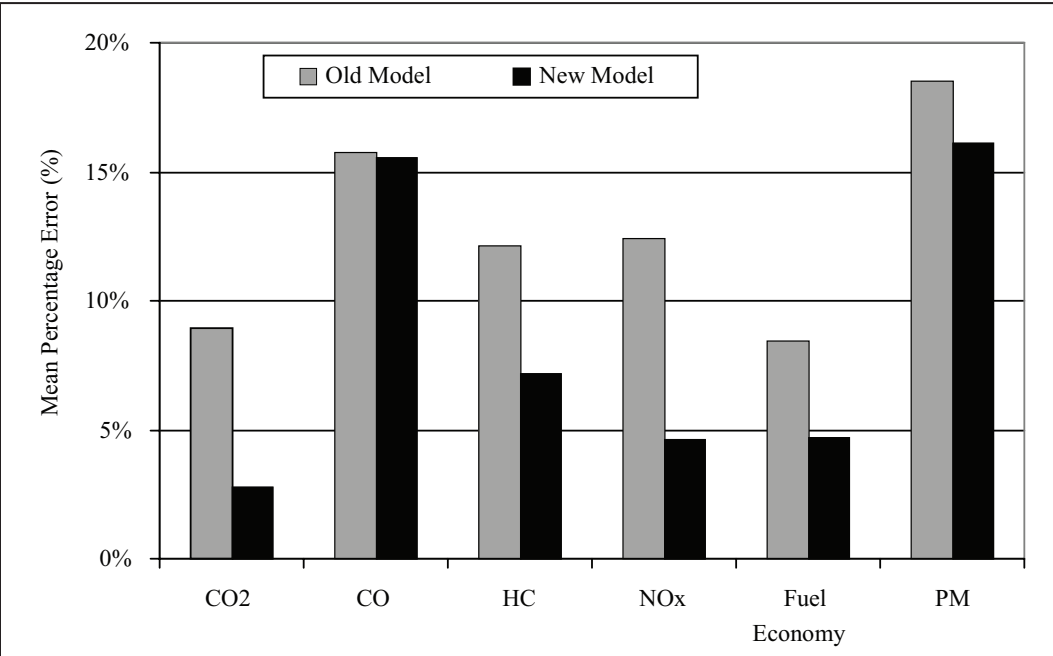


Figure 3: Mean Percentage Errors Comparison Between Old and New Models



CONCLUSION

A detailed correlation analysis was performed to investigate the relationships between duty cycle metrics and emissions and fuel economy and to identify the most important parameters for modeling. From an initial full correlation analysis of 13 cycle metrics, the number of metrics considered most useful for modeling was reduced to six. They are average speed with idle, percentage idle, stops per mile, standard deviation of vehicle speed, kinetic intensity, and average acceleration. Further analysis using non-parametric Spearman’s correlations between the six selected cycle metrics with emission and fuel economy shows that average acceleration has the weakest correlation, implying that its ability to predict emissions and fuel economy is less significant. Results from the regression analysis show how adding selected cycle metrics to average speed (with idle) improves the regression models. The results of this study could assist in determining appropriate strategies for later IBIS development and implementation of a transit fleet model.

This study shows that duty cycles have significant impacts on emissions and the fuel economy of transit buses, and it provides a useful framework for the selection of the most influential cycle metrics for modeling. Beside average speed, other cycle metrics such as stops per mile, percentage idle, standard deviation of vehicle speed, and kinetic intensity were found to be important and could be used to predict emissions and fuel economy better. From a green environment and energy efficiency viewpoint, this study suggests that if drivers could operate their vehicles less aggressively, spend more time in cruise mode, have less stop-and-go patterns, or less idling behavior while parking, exhaust emissions and fuel consumption from the transportation sector could be reduced, and air quality and energy efficiency could be improved.

APPENDIX A

AeroV	Aerodynamic Speed
ART	Arterial Cycle
AspedWID	Average Vehicle Speed with Idle
AspedWoID	Average Vehicle Speed Without Idle
AveAcc	Average Acceleration
AveDec	Average Deceleration
Average Speed	Average Vehicle Speed with Idle
BEELINE	Westchester County NY Beeline Cycle
BRAUN	Braunschweig Cycle
CARB	California Air Resources Board
CBD	Central Business District Cycle
CFR	Code of Federal Regulations
CharAcc	Characteristic Acceleration
CNG	Compressed Natural Gas
CO	Carbon Monoxide
CO ₂	Carbon Dioxide
COMM	Commuter Cycle
EMFAC	EMission FACtors Model
EPA	Environmental Protection Agency
ETC	European Transient Cycle
ETC_12	European Transient Cycle – Urban and Rural Segments
FTA	Federal Transit Administration
FuelEco	Fuel Economy
GVW	Gross Vehicle Weight
HC	Hydrocarbon
IBIS	Integrated Bus Information System
KInt	Kinetic Intensity
MAN	Manhattan Bus Cycle
MaxAcc	Maximum Acceleration
MaxDec	Maximum Deceleration
MOBILE6	Mobile Source Emission Factor Model
MOVES	Mobile Vehicle Emission Simulator
mph	Miles per Hour
MY	Model Year
NOx	Oxides of Nitrogen
NYBUS	New York Bus Cycle
NY-COMP	New York Composite Cycle
OCTA	Orange County Transit Authority Cycle
PercID	Percentage Idle
PM	Particulate Matter

Stops/Mi	Number of Stops per Mile
Stops/mile	Number of Stops per Mile
TransLab	Transportable Heavy-Duty Vehicle Emission Laboratory
UDDS	Urban Dynamometer Driving Schedule
VMY	Vehicle Model Year
VstdWID	Standard Deviation of Vehicle Speed with Idle
VstdWoID	Standard Deviation of Vehicle Speed without Idle
WMATA	Washington Metropolitan Area Transit Authority

Acknowledgments

The authors are grateful to the Federal Transit Administration of the US Department of Transportation for sponsoring this research effort. The authors are also grateful to all researchers and staff at WVU who contributed to the acquisition of experimental emissions data.

References

Ahn, K., H. Rakha, A. Trani, and M. Van Aerde. "Estimating Vehicle Fuel Consumption and Emissions Based on Instantaneous Speed and Acceleration Levels." *Journal of Transportation Engineering* 128, no. 2 (2002): 182-190.

Andre, M. and C. Pronello. "Relative Influence of Acceleration and Speed on Emissions under Actual Driving Conditions," *International Journal of Vehicle Design* 18, no. 3-4 (1997): 340-353.

Boriboonsomsin, K. and W. Uddin. "Simplified Methodology to Estimate Emissions from Mobile Sources for Ambient Air Quality Assessment." *Journal of Transportation Engineering* 132, no. 10 (2006): 817-828.

CARB (California Air Resources Board). *User's Guide to EMFAC2007*, Sacramento, CA, November 2006.

Clark N.N., A. Tehranian, R.P. Jarrett, and R.D. Nine. "Translation of Distance-Specific Emissions Rates between Different Heavy Duty Vehicle Chassis Test Schedules." Presented at Spring Fuels & Lubricants Meeting & Exhibition, May 2002, Reno, NV, SAE Paper No. 2002-01-1754.

Clark, N.N. and P. Gajendran. "A Predictive Tool for Emissions from Heavy-Duty Diesel Vehicles." *Environmental Science & Technology* 37, no. 1 (2003): 7-15.

Clark, N.N., D.W. Lyons, R.M. Bata, M. Gautam, W.G. Wang, P. Norton, and K. Chandler. "Natural Gas and Diesel Transit Bus Emissions: Review and Recent Data." Presented at SAE Truck and Bus Conference, Cleveland, OH, November 1997, SAE Paper 973203.

Clark, N.N., J.M. Kern, C.M. Atkinson, and R.D. Nine. "Factors Affecting Heavy-Duty Diesel Vehicle Emissions." *Journal of Air & Waste Management Association* 52, no. 1 (2002): 84-94.

Clark, N.N., W.S. Wayne, ABM S. Khan, D.W. Lyons, M. Gautam, D.L. McKain, G. Thompson, and R.A. Barnett. "Effects of Average Driving Cycle Speed on Lean-Burn Natural Gas Bus Emissions and Fuel Economy." Presented at SAE Fuels and Emissions Conference, Cape Town, SOAFR, January 2007, SAE Paper No. 2007-01-0054.

DieselNet. "Emission Test Cycles." Accessed in September 2007. <http://www.dieselnets.com/standards/cycles>.

Freund, R.J., R.C. Littell, and L. Creighton. *Regression Using JMP*. SAS Publishing, June 11, 2003.

Gautam, M., N.N. Clark, W. Riddle, R. Nine, W.S. Wayne, H. Maldonado, A. Agrawal, and M. Carlock. "Development and Initial Use of a Heavy-Duty Diesel Truck Test Schedule for Emissions Characterization." *Journal of Fuels and Lubricants* 111 (2002): 812-825.

Gillespie, T.D. *Fundamentals of Vehicle Dynamics*. Society of Automotive Engineers, Warrendale, PA, 1992.

Graboski, M.S., R.L. McCormick, J. Yanowitz, and L. Ryan. "Heavy-Duty Diesel Vehicle Testing for the Northern Front Range Air Quality Study." Final Report, Colorado Institute for Fuels and High-Altitude Engine Research, Colorado School of Mines, Golden, CO., 1998.

Kahaner, D., M. Cleve, and N. Stephen. *Numerical Methods and Software*. Prentice Hall, 1988.

Khan, ABM S., N.N. Clark, G.J. Thompson, W.S. Wayne, M. Gautam, D.W. Lyons, and D. Hawelti. "Idle Emissions from Heavy-Duty Diesel Vehicles – Review and Recent Data." *Journal of the Air & Waste Management Association* 56 (2006): 1404-1419.

Khan, ABM S., N.N. Clark, W.S. Wayne, M. Gautam, G. Thompson, D.L. McKain, D.W. Lyons, and R.A. Barnett. "Weight Effect on Emissions and Fuel Consumption from Diesel and Lean-Burn Natural Gas Transit Buses." Presented at Asia Pacific Automotive Engineering Conference, Hollywood, CA, August 2007, SAE Paper No. 2007-01-3626.

Miller, J.M. *Propulsion Systems for Hybrid Vehicles*. The Institution of Engineering and Technology, London, UK, 2004.

Nine, R.D., N.N. Clark, and P. Norton. "Effect of Emissions on Multiple Driving Test Schedules Performed on Two Heavy Duty-Vehicles." Presented at SAE Fall Fuels and Lubricants Meeting and Exposition, Baltimore, MD, October 2000, SAE Paper No. 2000-01-2818.

Nine, R.D., N.N. Clark, C.M. Atkinson, and J.J. Daley. "Development of a Heavy Duty Chassis Dynamometer Driving Route." *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering* 213 (1999): 561-574.

O'Keefe, M.P., A. Simpson, K.J. Kelly, and D.S. Pedersen. "Duty Cycle Characterization and Evaluation Towards Heavy Hybrid Vehicle Applications." Presented at SAE World Congress & Exhibition, Detroit, MI, April 2007, SAE Paper No. 2007-01-0302.

Rakha, H. and Y. Ding. "Impact of Stops on Vehicle Fuel Consumption." *Journal of Transportation Engineering* 129, no. 1 (2003): 23-32.

SAE International. "Fuel Economy Measurement Test (Engineering Type) for Trucks and Buses." *SAE J1376*, 1982.

SAE International. "Recommended Practice for Measuring Fuel Economy and Emissions of Hybrid-Electric and Conventional Heavy-Duty Vehicle." *SAE J2711*, 2002.

SAS Institute Inc. *JMP® 8 Statistics and Graphics Guide. Second Edition*, Cary, NC, 2009.

Schiavone, J.J., W.S. Wayne, R.D. Nine, and N.N. Clark. "Development of Bee-Line Transit Bus Dynamometer Driving Schedule." Interim Task Report, Submitted to Westchester County Department of Transportation, October 2002.

Simpson, A. "Parametric Modeling of Energy Consumption in Road Vehicles." Ph.D. Thesis Submitted to the University of Queensland, Australia. Sustainable Energy Research Group, School of Information Technology and Electrical Engineering, February 2005.

Thompson, E.D., M. Ansari, and G.A. Eberhard. "A Truck and Bus Chassis Dynamometer Developed for Fuels and Lubricants Research." International Fuels & Lubricants Meeting & Exposition, Tulsa, OK, October 1990, SAE Paper 902112.

U.S. EPA. *User's Guide to MOVES2010a, Technical Report*, EPA420-B-10-036, Washington, D.C., 2010.

U.S. EPA. *User's Guide to MOBILE6.1 and MOBILE6.2, Technical Report*, EPA420-R-03-010, Washington, D.C., 2003.

Vora, K.A., N.N. Clark, R.D. Nine, M. Gautam, W.S. Wayne, G.J. Thompson, and D.W. Lyons. "Correlation Study of PM and NO_x for Heavy-Duty Vehicles Across Multiple Drive Schedules." Presented at SAE Powertrain & Fluid Systems Conference, Tampa, FL, October 2004, SAE Paper No. 2004-01-3022.

Wang, W.G., D.W. Lyons, N.N. Clark, M. Gautam, and P.M. Norton. "Emissions from Nine Heavy Trucks Fueled by Diesel and Biodiesel Blend Without Engine Modification." *Environmental Science & Technology* 34 (2000): 933-939.

Wayne, W.S., ABM S. Khan, N.N. Clark, D.W. Lyons, M. Gautam, and G. Thompson. "Effect of Average Speed and Idle Duration on Exhaust Emissions from a Diesel Bus Tested on Fourteen Drive Cycles." presented at Transportation Research Board Annual Meeting, Washington, D.C., 2007, Paper No. 07-2945.

Wayne, W.S., M.G. Perhinschi, N.N. Clark, S. Tamayo, and J. Tu. "Integrated Bus Information System (IBIS) – A Vehicle Procurement Resource for Transit." *Journal of the Transportation Research Board* 2233 (2011): 1-10.

Wayne, W.S., N.N. Clark, R.D. Nine, and S. Rosepiller. *Washington Metropolitan Area Transit Authority Diesel Emissions Control Retrofit Project*. Final Report, West Virginia University, Morgantown WV, September 2002.

Jun Tu is a Ph.D. candidate in the Center of Alternative Fuels, Engines, and Emissions at West Virginia University (WVU). He is currently involved in a project on Integrated Bus Information System, which includes the development of a transit fleet emissions prediction model for the Federal Transit Administration. This fleet emission model is to assist transit agencies in evaluating the emissions implications of their new transit vehicles. His research interests include emission inventory modeling and emission analysis for heavy-duty vehicles.

Scott Wayne joined the Department of Mechanical and Aerospace Engineering at WVU in 1997. Dr. Wayne's research interests focus on measuring and reducing emissions from heavy-duty vehicles. He presently serves as associate professor and director of the Transportable Heavy-Duty Vehicle Emissions Testing Laboratory at WVU. This one-of-a-kind laboratory travels throughout the nation measuring the emissions from heavy-duty trucks and buses. Data gathered by this laboratory are used by engine, vehicle, and after treatment manufacturers to evaluate alternative fuels and develop new engine technologies in an effort to reduce environmental pollution, as well as by state and federal agencies to set regulations limiting the emissions from mobile sources.

Mario G. Perhinschi received an M.S. degree in aerospace engineering from Georgia Institute of Technology, Atlanta, in 1994 and a Ph.D. degree in aerospace engineering from the Polytechnic University of Bucharest, Romania, in 1999. He is an associate professor with the Mechanical and Aerospace Engineering Department at WVU, Morgantown, currently teaching courses in flight modeling and simulation, controls, artificial intelligence, and mechatronics. His research areas of interest include modeling and simulation of aerospace systems, fault tolerant control systems, parameter identification, artificial intelligence techniques (genetic algorithms, fuzzy control, and neural networks), autonomous air vehicles, and handling qualities of fixed and rotary wing aircraft.

